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Use of Verified Twitter Accounts During Crisis Events

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USE OF VERIFIED TWITTER ACCOUNTS DURING CRISIS EVENTS

by

Kai Anderson

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ABSTRACT

Use of Verified Twitter Accounts During Crisis Events

by

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Utah State University, 2018

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Department: Computer Science

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To study the role verified Twitter accounts play in a crisis event, information was collected from Twitter’s API (Application Programming Interface) from February 28, 2018 through March 3, 2018 during a powerful storm on the East Coast of the United States called a Nor’easter. Through data collection and analysis, this thesis describes how verified Twitter accounts communicated during a crisis event. Three exploratory questions were proposed to better understand the use of verified Twitter accounts: *Who are the verified Twitter users that tweet about a crisis event? What types of information do verified Twitter users tweet about a crisis event? When do verified Twitter users tweet*

about a crisis event? Results show that verified Twitter accounts create more original messages, share more informative messages, and spread less spam than their non-verified counterparts.

PUBLIC ABSTRACT

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Kai Anderson

CONTENTS

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Social media have become a growing communication venue in everyday life as well as during crisis events [1]. For example, Twitter had 200 million messages (tweets) a day in 2011 [2] and an estimated 500 million messages (tweets) a day in 2017 [3]. During a crisis event, Twitter often sees topics trending around the event (e.g., messages that contain relevant hashtags like #hurricane #harvey). Social media can support a crisis - event response by improving situational awareness and facilitating community or group communication [4], [5]. However, the proliferation of social media content during a crisis event also poses the challenge of information overload. With so much data, how can crisis response groups or affected users find relevant and reliable information from social media? One method for sifting through this data is to reduce the volume to more manageable levels by focusing on content from particular types of users [6].

This research is exploratory and investigates the use of verified Twitter accounts during crisis events. Verified Twitter accounts are those accounts that Twitter has investigated and found to be genuinely maintained by the claimed owner. Celebrities, public officials, and other well-known persons or companies often seek this account status so that others know messages are really coming from them and not a fake account. Because their owners have high public visibility, verified accounts attract more attention from Twitter users which typically leads to a larger number of followers. In short, verified users seem to have more voice on Twitter because on average their tweets reach a much larger audience than a non-verified account. The owners of these accounts may also have greater accountability to provide accurate or relevant information because they represent a brand, whether themselves or an organization. Thus, verified Twitter accounts would seem to be sources of information that have high visibility and influence as well as sources that are perhaps more trustworthy. For these reasons, this thesis aims to understand the use of verified Twitter accounts surrounding crisis events.

1.1 Research Questions

To better understand the use and influence of verified Twitter accounts during crisis events, we address several exploratory research questions:

1. *Who are the verified Twitter users that tweet about a crisis event?*
2. *What types of information do verified Twitter users tweet about a crisis event?*
3. *When do verified Twitter users tweet about a crisis event?*

Answering these questions will help us better understand who these verified Twitter users are and what kinds of information they share during a crisis event. In turn, a better understanding of the activity of verified Twitter users will help us to better assess the usefulness of verified Twitter user activity during a crisis event.

1.2 Research Overview

To study the role verified Twitter accounts play in a crisis event, we used the Twitter API (Application Programming Interface) to collect tweet data about a crisis event. The event for observation was a storm that hit the East Coast of the United States on March 1st through March 3rd, 2018. After the information was collected, the types of verified Twitter accounts that posted during the event were classified and analyzed. The tweets from the verified accounts were also classified and analyzed. Our goal was to collect the most relevant information and data possible on the use of verified Twitter accounts social media activity during crisis events. The research is exploratory in nature and as such the research questions are broad to give an overview of verified account behavior. The terms account and user are both used to represent the Twitter account and its screen name, throughout this thesis.

1.3 Thesis Overview

This thesis document contains four additional chapters following this introduction. Chapter 2 contains the literature review and background information needed to understand the research. Chapter 3 details the data collection method and includes the resulting data for analysis. Chapter 4 answers the research questions and displays the results obtained from the analysis. Chapter 5 concludes the thesis with a summary, limitations of the research, and possibilities for future work.

CHAPTER 2

LITERATURE REVIEW

Literature guiding this thesis research plan as well as literature providing insight into the current spectrum of crisis informatics are detailed in this chapter.

2.1 Crisis Informatics

Social media impact disaster and crisis response because they facilitate communication and information exchange between communities, groups, and individuals [1]. The research field of *crisis informatics* has recently emerged to study how people use information communication technologies (ICTs) like social media during crisis events [7]. The field of crisis informatics began in the early 2000's when Internet use became more commonplace. Through blogs, websites, and eventually social media (e.g., Facebook, Flickr, Twitter, etc.) individuals and groups could communicate during crisis events [8]–[10]. Research shows that using crisis generated social media information can improve disaster response and recovery efforts [11], [12].

2.2 Twitter

Twitter is a large network for connecting with millions of people simultaneously which can have a profound impact on communication during crisis or natural disaster. Users can connect by "following" other users or through trending topics (e.g. SuperBowl or #flooding). Because of the high volume of tweets, around 500,000,000 a day in 2017

[3], analyzing the information has proven difficult. Research into digesting large data sets from Twitter is ongoing [13]–[15].

Twitter regularly publishes blogs on topics such as crisis informatics, Twitter's growth, and the use of Twitter during popular cultural events. From the official twitter blog, Twitter teamed up with Oxfam India for a crisis informatics conference:

> *"While natural disasters can undoubtedly cause widespread humanitarian havoc, a lot can be done for the victims - even from outside the crisis zone. Through the #TweetToTransform initiative, Oxfam India's targeted collaboration with Twitter is designed specifically to highlight best practices in disaster management and public communication" [16].*

The blog states that using Twitter during crisis events is effective because Twitter is a robust communication network that can mobilize people in real-time. Mahima Kaul, Twitter India's Head of Public Policy stated,

> *"We saw an incredibly powerful example of this (Twitter's ability to assist crisis response) during the Tsunami in Japan in 2011, when Twitter users shared countless Tweets about the scope of the impact zone, updates about the safety of friends and family, and conversed moment-by-moment on the status of the disaster as it unfolded."*

Connecting users during a crisis event is perhaps the most difficult problem when leveraging Social Media for communication. One solution is to follow a hashtag which allows users to see other's public posts relating to a particular topic, which could then lead people to collaborate and communicate about that topic.

2.3 Collecting Crisis Event Communication

To understand the use of Twitter and verified accounts during a crisis event, data needs to be collected from a real event. Twitter data collection is done through an API (Application Programming Interface) that queries Twitter based on keywords, location, user, etc. However, finding relevant data can be difficult because of the volume of tweets.

Research shows crisis responders are better able to collect relevant data if they view users as stakeholders that are interested in the crisis event and connect with proactive users making reports [17]. For example, vocal Twitter volunteers willing to report, vet, and pass on important information could use the keyword “#help” in the tweet text to connect their crisis event with crisis responders. These “Digital Volunteers” emerge during crisis events through a desire to help and a desire to inform the community of a crisis event and its details [18]–[20]. In this regard, each Twitter user is a potential worker in a large distributed data problem where the act of vetting data and reporting comes from the verified user’s desire to do good. This type of digital volunteering is similar to the phenomenon that a witness to an accident will call emergency services. Gaining insights into the use of verified accounts may also show some useful trends in crisis data reporting and collecting.

2.4 Classifying Data

Classifying data will assist in understanding the use and context of tweets from verified Twitter accounts. Previous research discusses the automatic classification of tweets as an ongoing area of research within the space of crisis informatics and machine learning [15]. One study of the 2010 Haiti earthquake shows how automatic text classification has several obstacles that makes it difficult to correctly classify and pass along text data, like tweets [21]. The issues reside in the fact that the text is short (tweets can be 140 characters or in the United States as of November 2017 - 280 characters [22]), topics from gathered messages can often be unrelated, and contextual information may be missing. Training the algorithms that handle data classification is difficult; information gathered may be small and variation in crisis events may make an algorithm less effective for all events [21]. Understanding the use of verified Twitter accounts may assist in improving the machine learning process of automatic tweet classification by improving the data relevance.

2.5 Sentiment Analysis

Sentiment analysis is another tool for understanding Twitter data. Sentiment analysis is the computational analysis and categorization of opinions expressed in a piece of text. A common categorization might include positive, negative, or neutral words towards a topic [23]. Sentiment analysis has also been used to understand customer perception of a product, predict financial performance, understand election outcomes, and as input for disaster response systems [24]. For example, in 2015 researchers used sentiment analysis during the MERS (Middle East Respiratory Syndrome) outbreak in South Korea to successfully record fear, sadness, disgust, happiness, surprise, and anger in tweets about the outbreak and map it over time [25]. The result gave confidence in analyzing public opinion through sentiment analysis.

2.6 Verified Twitter Accounts

Collecting relevant data more efficiently and understanding crisis event communication led to our research around the behavior of verified users during crisis events. Motivated by the verified status of the account, tweets may contain more relevant crisis data that is vetted by the verified account holder.

Twitter’s website states the following about verified Twitter accounts:

“*An account may be verified if it is determined to be an account of public interest. Typically, this includes accounts maintained by users in music, acting, fashion, government, politics, religion, journalism, media, sports, business, and other key interest areas. A verified badge does not imply an endorsement by Twitter.”*

To identify a verified Twitter account a blue badge will be displayed by tweets from the account and the Twitter API includes a field indicating the verified status.

Verified Twitter accounts have value because it is not possible to simply create a verified account. The effort to obtain a verified Twitter account has changed over time and is at the discretion of Twitter. At the time of writing this thesis, the ability to request verified status through an online form has been removed, although account verification is still possible when Twitter proactively sees activity that deems it necessary to provide a verified account [26]. Verified accounts also have a set of rules (terms of service) that is strictly enforced because of the representative nature of the accounts. An infraction against the terms of service from a verified account will result in the loss of the account or the verified status of the account [27].

Previous research into finding reliable information on Twitter found that that users with many previous messages, a large number of re-tweets, and a bio that is attached to the account are more likely to share reliable information [28]. Those qualities, while not only found in verified accounts, are manifest often in verified Twitter accounts.

CHAPTER 3

METHODOLOGY

This chapter describes the methodology used to address the research questions in this study. First, we identified a crisis event for data collection: a large Nor'easter winter storm. Next, tweets about the storm event were collected using the Twitter streaming and search APIs. Analysis began by coding the content of the collected tweets and categorizing the verified account users who sent tweets during the Nor'easter. The following sections provide more detail about the methods we used to collect and analyze our research data.

3.1 Crisis Event of Study: A Nor'easter Storm

Crisis events vary in duration, area, severity, and number of affected people. When looking for a crisis event to study, we searched for an event that would generate significant activity on Twitter (but not too much) so that we would have a large enough data sample to study. We chose to collect Twitter data during the Nor'easter storm that hit the north-eastern United States on March 1st, 2018 (see Figure 1 for an image of the storm). A Nor'easter is a storm on the eastern coast of the United States named for the wind that comes from the northeast [29]. Some well-known Nor'easters include the Blizzard of 1888, the "Ash Wednesday" storm of March 1962, the New England Blizzard of February 1978, the March 1993 "Superstorm," and the recent Boston snowstorms of January and February 2015. Past Nor'easters have been responsible for billions of dollars in damage, disruption of services, and serious coastal flooding. From March 1st until its dissipation on March 3rd, this Nor'easter caused over 2 million people to lose power, thousands of cancelled flights and trains, school closures, at least eight deaths, and coastal flooding [30]. Most of the storm damage was caused by flooding on the coast at high tide, 90+ MPH wind gusts, and up to 39" of snow [31].

Figure 1 - Satellite image of the Nor'easter on March 2, 2018 [32].

The Nor'easter caused a worldwide trending hashtag (#noreaster) on Twitter from late on February 28th, 2018 until March 4th, 2018 (leading up to and during the course of the storm) [33]. To collect data on the event, some initial searching on Twitter was required to find keywords, hashtags, and location data. This Nor'easter was beyond the scope of Twitter's location-based search API, which is limited to a 25-mile radius. Thus, we relied on keyword and hashtag searches. The total area hit by the storm included Canada's East Coast, Connecticut, Delaware, Maine, Maryland, Massachusetts, New

Jersey, New York, Pennsylvania, Rhode Island, Virginia, and Washington D.C.; the storm affected a total of 80 million residents [34].

3.2 Data Collection

Twitter's API gives a user the ability to search for tweets based on location, time, user ID, keyword, etc. The result of the call includes the date, tweet text, user info, location, hashtags, URLs, verified status, etc. The structure shown below in Figure 2 is the resulting JSON object from a Twitter API query.


```
{
  "tweet": {
    "created_at": "Thu Apr 06 15:24:15 +0000 2017",
    "id_str": "850006245121695744",
    "text": "1\/ Today we\u2019re sharing our vision for the future of the Twitter API platform!
    "user": {
      "id": 2244994945,
      "name": "Twitter Dev",
      "screen_name": "TwitterDev",
      "location": "Internet",
      "url": "https:\/\/dev.twitter.com\/",
      "description": "Your official source for Twitter Platform news, updates & events. Need tec
    },
    "place": {

    },
    "entities": {
      "hashtags": [

      ],
      "urls": [
        {
          "url": "https:\/\/t.co\/XweGngmxlP",
          "unwound": {
            "url": "https:\/\/cards.twitter.com\/cards\/18ce53wgo4h\/3xo1c",
            "title": "Building the Future of the Twitter API Platform"
          }
        }
      ],
      "user_mentions": [

      ]
    }
  }
}
```


Figure 2 - Format of Twitter API JSON.

Once the crisis event characteristics (location, keywords, etc.) were understood the collection of data could begin. Data collection was completed with two Python scripts that directly queried the Twitter API. The first script made calls to the Twitter Search API and returned search results from past Twitter data. For example, making a query with the term “noreaster” returned tweets about the recent Nor’easter storm. The Twitter Search API is not an exhaustive source of tweets. A limitation to the Twitter Search API is that it only returns tweets sent in the last week when searching by location or keyword (searching for a specific user’s tweets allows a much longer history). Promptness when running the search script gave us results from February 25th until after the storm had dispersed.

The second script collected newly generated tweets using Twitter’s Streaming API, which collected real-time Twitter data using the same types of queries as the Search API (i.e., searching by location, keyword, hashtag, user ID, etc.). The API works by establishing a connection to the Twitter service, making a long-lived HTTP request and parsing the response incrementally. The response to the HTTP request is near real-time tweets that have been filtered according to the request parameters [22]. Results from the streaming API made the total data collection from Feb 25th through March 14th. To ensure thorough data collection, multiple search queries were executed and the data set is robust under the limitations the Twitter service imposes.

Leading up to the storm and throughout the duration of the storm, the scripts using Twitter’s API returned 76,093 tweets discussing the Nor’easter or including the hashtag “#noreaster.” Tweets from verified users numbered 5,123 in the same period, comprising 6.7% of the returned results.

3.3 Data Analysis

Once the data collection was complete, analysis of the results began. We addressed the research questions through categorizing tweets, automated sentiment analysis, investigating the type of account the verified user represents, and plotting the results. These steps are described in more detail below. Results will follow in chapter 4.

3.4 User Categorization

Verified accounts represent a person, company, or organization. To better understand the research question of "*Who are the verified Twitter users that tweet about a crisis event?",* each user was examined and sorted into categories. The verified users were categorized by the description given on the account (i.e., CEO of Microsoft, news anchor, comedian, journalist, etc.). If verified users could not be categorized through their account description, we looked at their tweet history and/or searched the internet by their account name to understand the type of person or organization each account represents. Categories evolved inductively as the users were identified and sorted into groups (e.g., news media, celebrity, business, etc.) using content analysis and grounded theory techniques [35], [36]. The results of this analysis are reported in section 4.1.

3.5 Tweet Topic Categorization

Next, we examined the content of the messages sent by verified accounts to answer the following question: *What types of information do verified Twitter users tweet about a crisis event?* After reading each of the verified account tweets, categories were derived inductively. The categories evolved as we iteratively revisited our coding scheme.

Categories coded included forecasts, entertainment, offers of aid, offers of advice, reporting damage or closures, etc. This categorization of the tweet content let us examine what types of information verified accounts share to address our research questions. Using this data and methodology allowed us to compare the types of information sent by different kinds of verified accounts. Insights from our analysis may indicate the importance of following verified Twitter accounts during a crisis event.

Another method we used for understanding the content of what verified accounts tweet is sentiment analysis. To analyze these tweets, we used the TextBlob python library for Natural Language Processing which includes sentiment analysis using the NLTK (Natural Language Toolkit) language data and corpus [37]. More details on sentiment analysis is included in the Literature Review.

Tweet topic categorization is reported and analyzed in section 4.2. Additionally, we also compared verified account activity with a sample of non-verified account activity to understand how verified accounts differ or do not differ from non-verified accounts. This analysis examines differences in tweet topics, how informative tweets are, sentiment analysis, and word count.

CHAPTER 4

DATA ANALYSIS AND RESULTS

The following chapter answers the research questions based on the results of the data analysis. Each section includes the original research question, data relevant to the question (both verified and non-verified tweets), descriptions of the data, observations relating to the question proposed, and conclusions.

4.1 Who Are The Verified Twitter Users That Tweet About a Crisis Event?

Once categorization was complete we looked to better understand the types of verified Twitter accounts that tweeted during the Nor'easter. Patterns emerged from the data and groups logically formed based on the account biography and description. Because the collection was reviewed in chronological order, the first accounts to appear were news media accounts (e.g., news publications, anchors, journalists, and meteorologists). Shortly afterwards, other account types began to appear, starting with emergency services (fire and police departments) and then followed by businesses. Timelines of the Twitter activity of all account types involved are included in Appendix A and detailed later in section 4.3.

4.1.1 Account Type Categories

Account types were narrowed down to six distinct categories with defined characteristics. The category descriptions, number of accounts per category, and examples can be found in Figure 3 below.

Account Type	Total Accounts	Percentage of Total Verified Users	Description	Example Accounts
Business	198	10%	Represents a business; including officers and board members. Food, travel, technology, etc.	**@blueapron** - a food delivery service. **@Generac** - a Wisconsin company that produces backup generators.
Celebrity	113	6%	Represents a person; personal brand or personal achievements. Athletes, musicians, artists, etc.	**@THETOMMYDREAMER** - Wrestler. **@toddcarey** - Todd Carey, a musician.
Emergency Service	56	3%	Accounts belonging to fire stations, police, or government agencies involved in aid or protection.	**@FDNY** - official New York City Fire Department. **@fema** - Department of Homeland Security agency for supporting first responders.
News Media	1,446	73%	Accounts belonging to news publications or people employed by the publication; anchors, journalists, meteorologists, etc.	**@nytimes** - The New York Times news publication's official Twitter account. **@JaniceHuff4ny** - Chief Meteorologist at WNBC.
Organization	123	6%	Accounts representing an organization; whether private or government. Schools, clubs, community centers, museums, activist groups, etc.	**@NASA** - official Twitter account for the U.S. National Aeronautics and Space Administration. **@RutgersU** - official Rutgers University Twitter account. **@PennDOTNews** - The official Twitter account for the PA Department of Transportation. **@NERL** - National Renewable Energy Laboratory.
Politician	33	2%	Elected government officials presiding over a constituency. Governor, Senator, Congressional Representative, Mayor, etc.	**@CoryBooker** - U.S. Senator from New Jersey. **@NYCMayorsOffice** - Tweets from the New York City Mayor and staff on his behalf. **@RepEspaillat** - New York's 13th Congressional District Representative.
Total	1969			

Figure 3 - Verified User Account Categories and Statistics

4.1.2 Activity by Account Type

Results show that *news media* accounts made up the majority of verified accounts tweeting about the crisis event. The total number of tweets per category will differ from the number of accounts per category because accounts have varying activity levels. For example, *@NBCNewYork* (a *news media* publication) tweeted the most about the Nor'easter with a total of 65 tweets between February 28, 2018 and March 3, 2018. The total number of tweets from each category is detailed in the following figure.

Account Category	Number of Tweets	Percentage of Verified Tweets	Percentage of Total Tweets Collected
Business	398	8%	0.5%
Celebrity	165	3%	0.2%
Emergency Service	166	3%	0.2%
News Media	4,165	81%	5.4%
Organization	173	3%	0.2%
Politician	54	1%	0.1%
Total	5121		6.7%

Figure 4 - Number of Tweets by Account Category

From February 28, 2018 through March 3, 2018, verified Twitter accounts tweeted about the Nor'easter 5,121 times and 4,165 of those tweets were from accounts representing *news media*. When looking at who is tweeting during the Nor'easter, it is also interesting to look at all the tweets that were collected, not just tweets from verified accounts. With this perspective, Figure 5 below shows the percentage of each category compared with all verified tweets. Figure 6 includes all non-verified tweets (70,972) to help visualize the data set we are interested in compared with the entire data collection results.

4.1.3 Account Type Observations

When research began, we expected a larger number of celebrities and official representative accounts like politicians to be tweeting during a crisis event. We expected *news media* accounts, but we did not expect the amount of activity or number of accounts involved with this category. In hindsight, one might expect that *news media* accounts would play a significant role in distributing information during a crisis event. Forecasts began appearing first in conjunction with the possible Nor'easter several days before the event and these forecasts came almost exclusively from *news media* accounts.

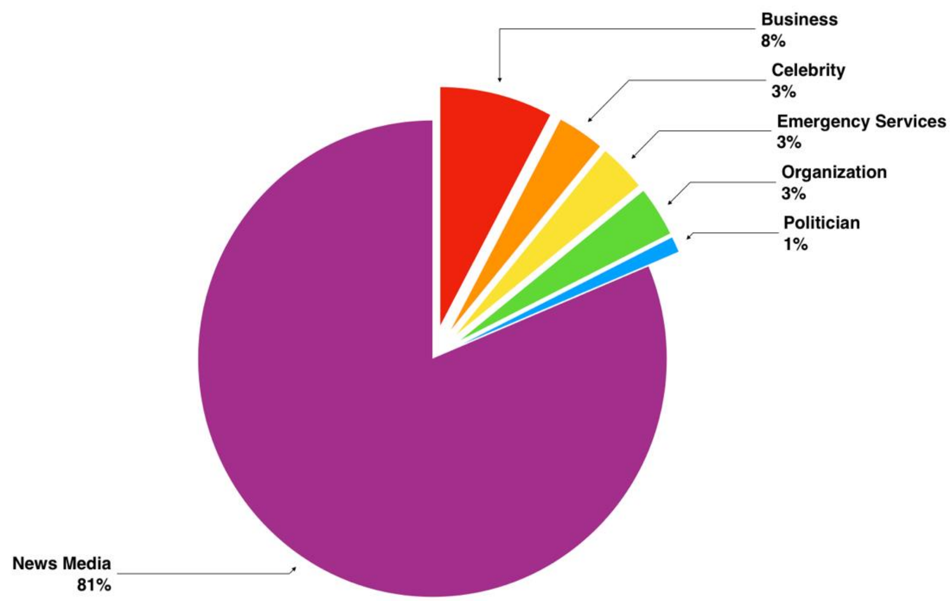

Figure 5 - Percentage of Verified Tweets by Category

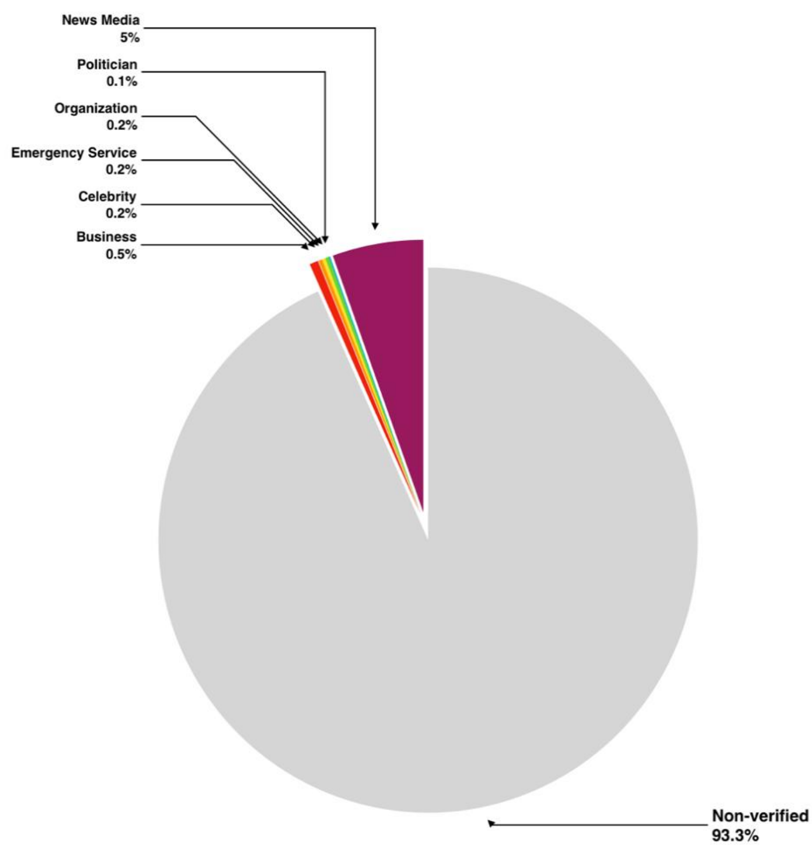

Figure 6 - Total Collection Percentages (76,093 Tweets)

When determining who was tweeting during the event, it became evident that some accounts almost always retweeted messages (a Twitter feature allowing a user to share another user's original content) and rarely provided original content. To understand this further, we looked at the retweet rates provided by the Twitter API. The field 'retweets' in the JSON tweet data gives the number of times the original message was retweeted. To enhance our view of retweets for visualizing an account's reach or visibility on Twitter we instead looked at only the retweet value of original tweets. We call this value organic retweets. All original tweets (non-retweeted) were analyzed for an organic retweet value. All verified tweets returned an average organic retweet number of 21.9, meaning every original tweet was retweeted an average of nearly 22 times. Contrasted with the non-verified organic retweet rate of 0.65.

The most retweeted message during the crisis event is shown in Figure 7. *@NASA* has a total of 28.9 million followers and created the most frequently retweeted tweets. Other notable retweet statistics showed that *organizations* and *politicians* held the most frequent organic retweet rate among verified accounts with around 32 retweets per message.

@nytimes has the highest number of followers totaling 41 million at the time of data collection. Among verified accounts in our collection, the average number of followers is 257,348 compared to an average of 3,457 followers for non-verified accounts. Thus, the average verified user has 74 times as many followers as a non-verified user. Insight into verified accounts and statistics of those users helps justify research into this subset of Twitter users. While making up only 6.7% of tweets on the Nor'easter, tweets from verified users on the Nor'easter are seen 500% more than the

non-verified Nor'easter tweets. Further analysis is included in section 4.3 where user types are analyzed on a timeline.

Figure 7 - The Most Retweeted Nor'easter Tweet

4.2 What Types of Information Do Verified Twitter Users Tweet About a Crisis Event?

The content of the tweets we collected were coded in the same way that user account categories were coded. Topic categories formed inductively as we read tweets. Themes emerged and we formed similar groupings as the coding scheme and categories were revisited. *Forecast*, a topic category, formed from *weather warnings, predicted measurements, and general forecasts* was combined into *forecast* as it became evident that topics would not require so much granularity.

4.2.1 Tweet Topic Categories

Figure 8 details the eventual topics that tweets were categorized into and descriptions with examples. For this crisis event, verified accounts began by tweeting weather forecasts and warnings. Because weather forecasters could predict the storm would happen a few days in advance, it is not surprising that the initial tweets were forecasts and weather warnings. Another crisis event (e.g. fire or earthquake) would likely begin with a different topic being tweeted first.

The following tweet was the first recorded in the timeframe by a verified account:

@NBCNewYork (Feb. 28 1:15 AM): A powerful nor'easter is expected to hit the tri-states toward the end of the week. Here's what you can expect and when: <link>

With the following reply from a non-verified user:

@Rebecca_Lambo: @NBCNewYork What the hell is a nor'easter I ain't got time for this #no

	Number of Verified Tweets	Percentage of Total Verified Tweets	Description	Examples
forecast	**1628**	**32%**	Weather forecast. Weather alert or warning. Weather prediction.	**@Sean_Breslin (3/1/2018 13:02):** *Were expecting an intense noreaster tomorrow and Saturday, with coastal flooding, strong winds and big snow total <LINK>* **@NBC10Boston (3/2/2018 00:15):** *Here is the projected path of the nor'easter beginning Friday: <LINK>*
advice/ education	**391**	**8%**	Advice to deal with and prepare for bad weather. Education on why the weather is happening and what to do about it.	**@NY1 (3/1/2018 23:13):** *#The city is urging drivers and pedestrians to avoid crossing areas where water levels are too high to cross safely. <LINK>* **@peta2 (3/2/2018 17:13):** *Storms can be DEADLY for animals Keep your companion animals INDOORS & if you evacuate, NEVER leave them behind*
aid/resources	**159**	**3%**	Resources to receive aid. Shelters, fire and police reaching out, phone hotlines, etc.	**@NBC10Boston (3/2/2018 14:03):** *Here are some important resources to know of during the storm <LINK>* **@GovernorsOffice (3/2/2018 21:33):** *@GovernorTomWolf* announced that the Commonwealth Response Coordination Center is activated to respond to the severe #NorEaster winter storm impacting the state with high winds and heavy snow.
official alert	**93**	**2%**	An official alert: evacuation, weather severity alert, national guard status, etc.	**@wbx (3/2/2018 01:39):** *Voluntary evacuation recommended on Plum Island ahead of nor'easter Friday<LINK>* **@CBSNewYork (3/2/2018 07:49):** *Mayor Issues Code Blue Amid Nor'easter Storm <LINK>*
report closures	**452**	**9%**	A tweet detailing a closure; closed highways, schools, businesses, airports, etc.	**@DCCulture (3/2/2018 12:20):** *Federal government closed today, Friday, and many museums also closed due to sustained high winds #noreaster <LINK>* **@TamsenFadal (3/2/2018 15:00):** *Full list of school closings for NY, NJ, and Connecticut <LINK> #SchoolClosings #noreaster*
report damage	**856**	**17%**	A tweet reporting physical damage needing repair. Fallen power lines, flooding, loss of power, damage to roads, etc.	**@BostonNewsMan (3/2/2018 13:39):** *@AssignGuy @deskon7 Power out in Vinnin Square in Swampscott #noreaster* **@News12NJ (3/2/2018 12:21):** *JUST IN: Hoboken train station taking on water as rain continues to fall <LINK>*
report status	**1086**	**21%**	A tweet detailing the user's personal status. Or tweets about what is going on around the user that is not reporting a closure or damage that requires aid.	**@matthewjbell (3/2/2018 19:39):** *Found this #EastBoston neighbor out for a leisurely kayak along surface streets in the middle of a #Noreaster* **@CrisLeeMaza (3/2/2018 21:51):** *Traveling by train for #noreaster. Will report back. <LINK>*
entertainment	**399**	**8%**	Tweets for the purpose of conversation; humor, banter, blame, memes, etc.	**@Bob_Grip (3/3/2018 6:08):** *Why is there no weather on the Weather Channel? #rhetoricalquestion #boston #noreaster* **@roywoodjr (3/3/2018 15:01):** *Real umbrellas step up. Fake umbrellas sit down. #NorEaster*
advertising	**58**	**1%**	Advertising a good or service using the trending topic nor'easter.	**@blueapron (3/2/2018 16:51):** *#Noreaster? No problem. <LINK TO ORDER FOOD>* **@VerizonSupport (3/2/2018 20:20):** *Don't let the weather keep your evening adrift. Use our FiOS app to stay connected #noreaster <LINK>*
spam	**0**	**0%**	Tweets unrelated to the crisis event but given public view by including a trending topic like "#noreaster".	Example taken from non-verified tweets: **@kbari*** (2/28/2018 13:03):** *#Benghazi #Parkland DEMOCRATS DESTROY #WednesdayWisdom #noreaster HAPPENING NOW #DeepState*

Figure 8 - Tweet Topic Categories and Statistics

4.2.2 Non-verified Account Activity

To best understand what verified users are tweeting about during a crisis event we need to also consider what non-verified accounts are tweeting during and about the crisis event. This contrast gave insight into the usefulness of following a verified source for crisis event information. To make a comparison, we sampled non-verified tweets at the same rate verified accounts were tweeting (e.g. 2.7% from 2/28, 12.2% from 3/1, etc.). The total sample of non-verified tweets that we categorized by topic was 1,168 (25% of the total volume of verified Tweets). Below we compare the rates by topic over the entire data collection.

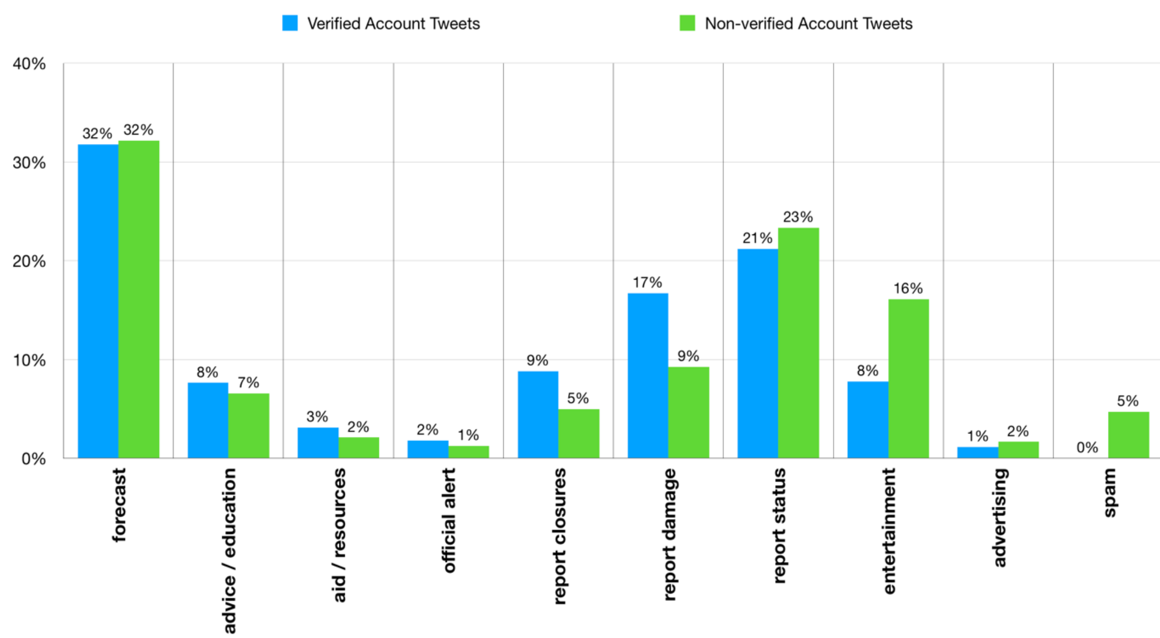

Figure 9 - Tweet Topic Percentages by Verified Status

4.2.3 Tweet Topic Statistics

By looking closely at the data obtained from the Nor'easter data collection, several trends are observable. The most obvious difference in the data sets of verified vs non-verified tweets is the rate of spam. It should be noted that advertising and spam are two closely related categories but differ in a distinct way. Advertising is a business (or other user type) opportunistically using the storm to move a product or service. We found that advertising remained relevant to the storm. For example, "here is how our service can benefit you in this Nor'easter." Spam is the use of a trending topic, like the Nor'easter, to push another agenda. The example given in Figure 8 above shows off-topic tweets given more views by including the trending Nor'easter. Spam was nonexistent in all 5,123 tweets from verified accounts.

Forecasts received the most attention and *reporting a status* was the second most tweeted topic. *Advice, aid, official alerts, reporting closures, and reporting damage* all were tweeted at higher rates by verified Accounts than the non-verified Tweet data we collected.

4.2.4 How informative is a topic and tweet?

In Figure 9 (above) the topics loosely move from informative topics on the left moving to less informative on the right. This is not a scientific measurement of usefulness but an observation based on using the Nor'easter subject to share information: Is the tweet about the Nor'easter? Is it spreading useful information like what to expect during the event? Does it provide aid or resources? The three topics on the right are found to be the least informative: *entertainment*, *advertising*, and *spam*. To visualize this method of categorization beyond the comparisons in Figure 9 we have grouped the non-informative topics and informative topics on a timeline in Figure 10.

- Informative topics: *forecast*, *advice/education*, *aid/resources*, *official alert*, *report closures*, *report damage*, and *report status*.
- Not informative topics: *entertainment, advertising,* and *spam*.

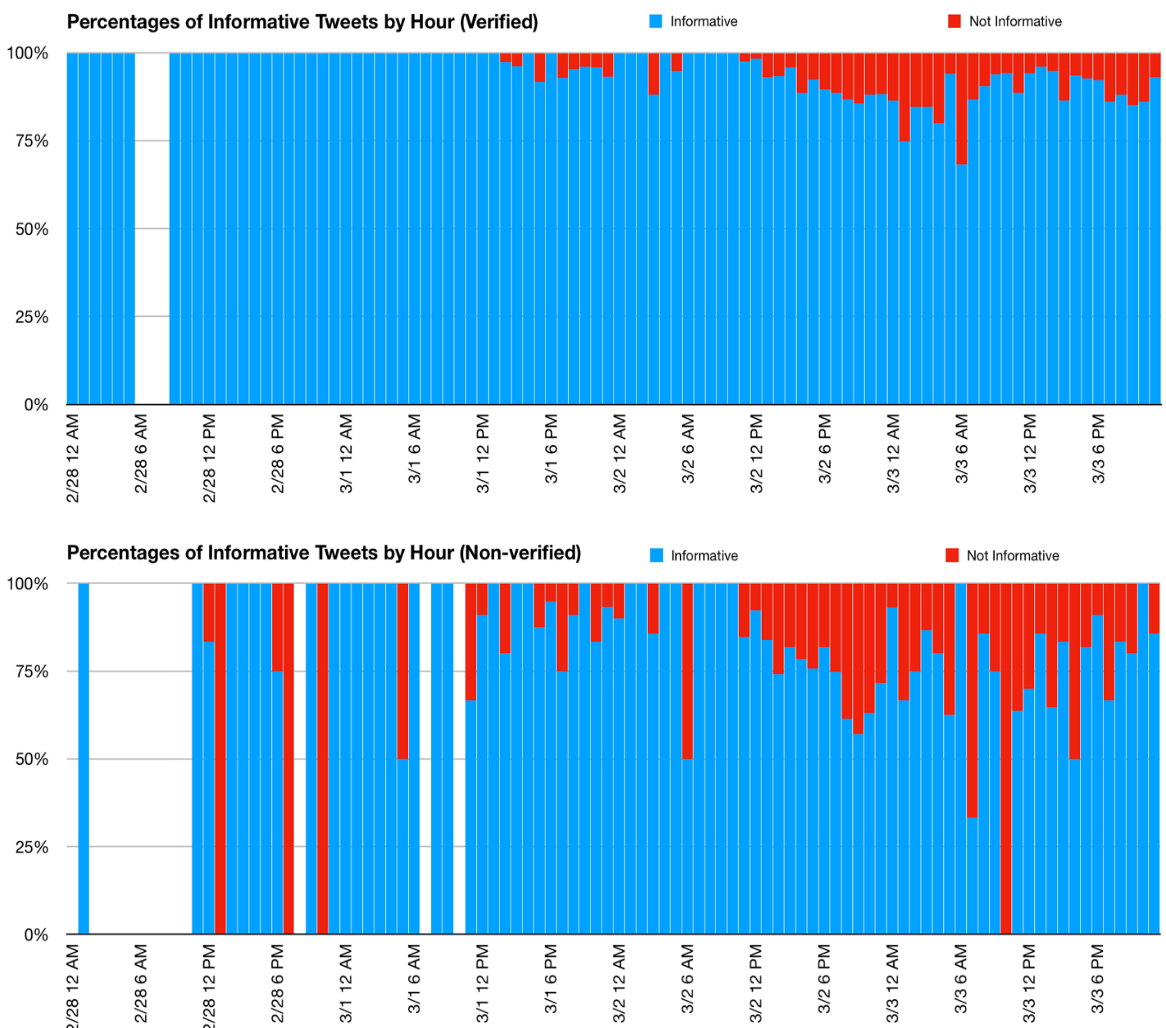

Figure 10 - Verified vs. Non-verified Informative Topics Timeline

Looking closely at Figure 10's two graphs, verified tweets have a trend of almost all informative topics up until the storm is in force on March 2nd. One explanation for the drop in informative tweets is the rise of entertaining stories about the storm. Two examples include some highly-shared images of broken umbrellas in the streets and a story where an airline pilot is quoted, "pretty much everyone on the plane threw up", reported in the early morning on March 2nd. The trends show that verified Twitter accounts are found to stay informative more consistently and more often than their non-verified counterparts.

4.2.5 Word Count Analysis

Word count analysis was done on verified and non-verified tweets about the Nor'easter. The figure below shows the top ten words used for both data sets.

Verified Tweets		Non-Verified Tweets	
Word	**Count**	**Word**	**Count**
noreaster	1682	noreaster	3083
winds	604	snow	1495
storm	538	nor'easter	1360
nor'easter	480	storm	1149
flooding	469	power	934
East	457	winds	766
Coast	410	East	681
snow	404	Coast	641
rain	403	flooding	603
power	394	rain	494

Figure 11 - Tweet Word Count Comparison with Verified Tweet Word Cloud

Both groups have identical top ten used words (although ordered differently). After filtering words common to sentence structure, we were given a list of the most counted words in our collection timeframe from both verified and non-verified accounts.

The popularity and use of similar words by both groups caused us to consider reasons why that might be the case. First, all the words in the top ten are status descriptions, adjectives of the Nor'easter, and locations which would likely span all users tweeting about the storm. The second observation on similar word count rates comes from looking at retweet rates as was done in section 4.1.

4.2.6 Retweet Rates and Their Effect on Analysis

To understand what may be happening, we look at the rates of original content (what percentage of tweets are original versus retweets). The rate of original content among our data set is 62% original content among verified accounts and 37% among non-verified accounts. That is a significant difference showing that non-verified accounts are not tweeting original content as often as verified accounts. For example, *@NASA's* most retweeted storm tweet had 1,710 retweets where only 42 of those retweets were by verified accounts in our collection and 1,456 were non-verified tweets in our collection (the other 200+ coming after data collection was over). This is one example of why there is so much overlap in common words, trending tweets that are often retweeted will span both verified users and non-verified users.

4.2.7 Sentiment Analysis Results

Finally, we look at sentiment analysis of Nor'easter tweets. Sentiment analysis, described in section 2.5 and section 3.5, uses a polarity score (between negative at -1.0 and positive at 1.0) of each tweet based on the entire tweet which shows emotions: positive, negative, or neutral. The second measure of sentiment is a subjectivity score: 0

means least subjective and 1.0 means most subjective. Subjectivity is the amount of opinion expressed in the tweet in the form of feelings, views, or beliefs.

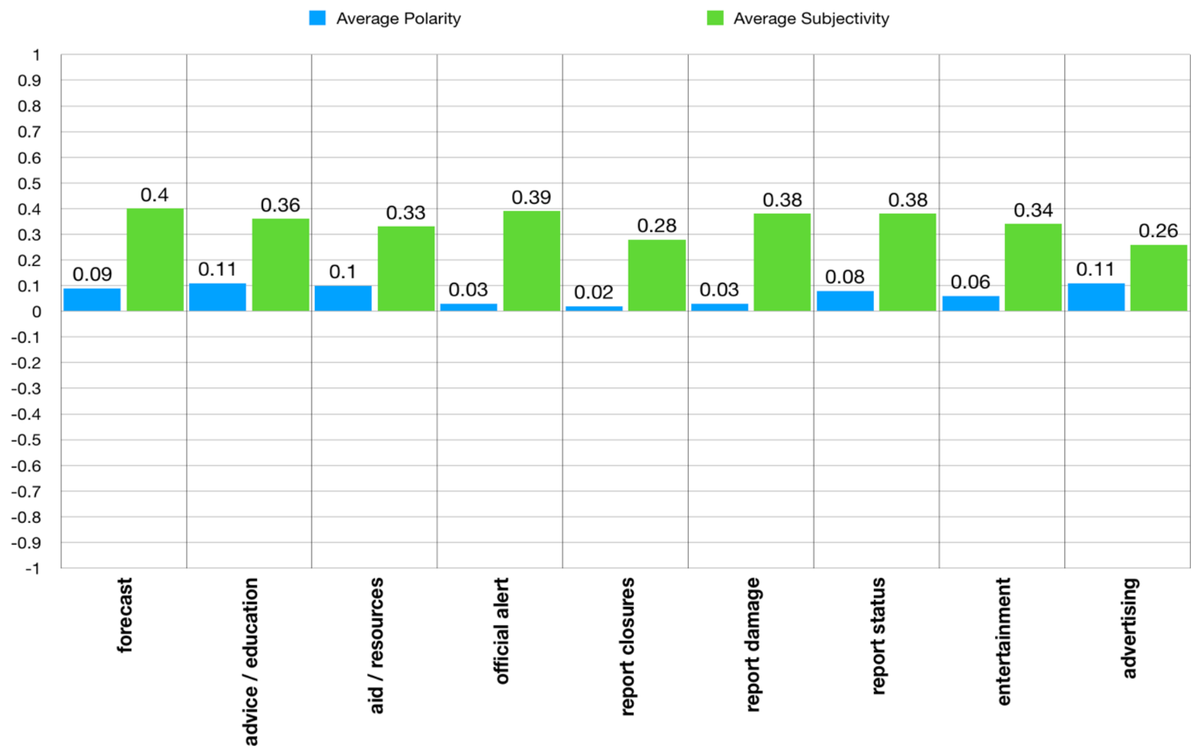

Figure 12 – Tweet Polarity and Subjectivity by Topic (Verified)

Based on Figure 12 and Figure 13 we can make several observations. Figure 12 shows polarity by tweet topic and the values do not differ much. Polarity for *reporting damage*, *reporting closures*, or *official alerts* are the lowest but all categories have an overall positive sentiment. Subjectivity among topics (also Figure 12) is very similar across all topics but with below average in *reporting closures* and *advertising*. It is difficult to make assumptions on causes and results based on this closely related data set. Although statements of facts in *reporting damage*, *reporting closures*, and *official alerts* do show a more neutral emotion which matches expectations based on topic categories.

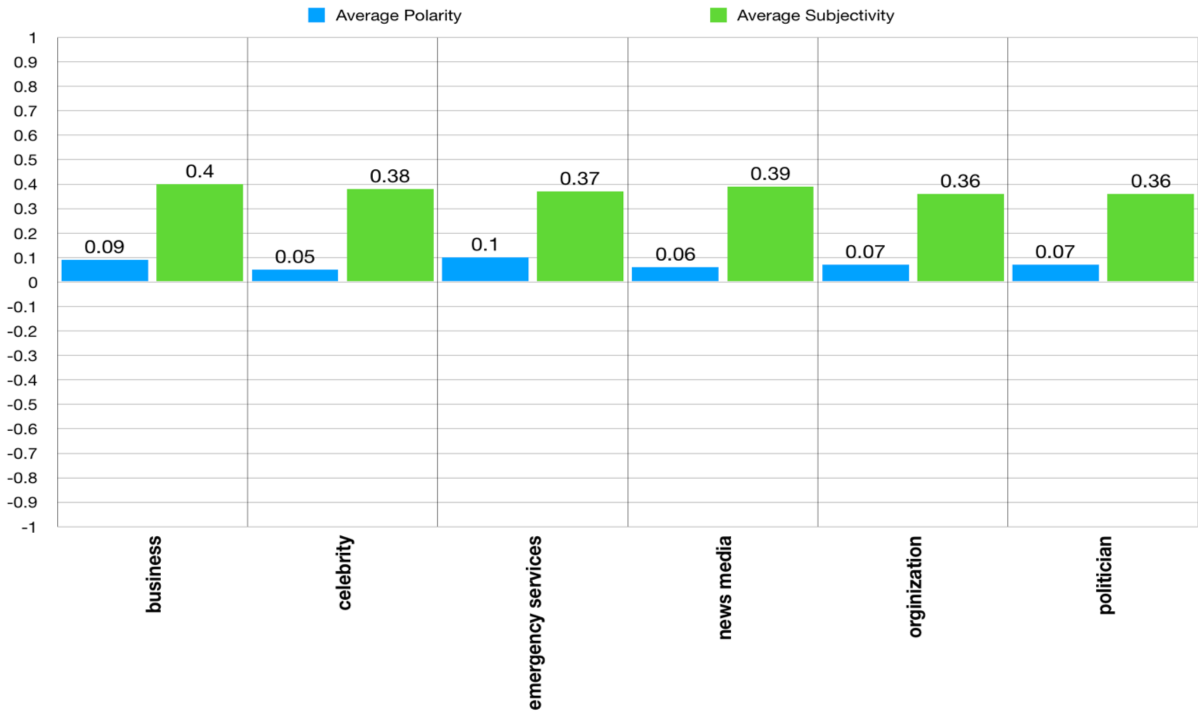

Figure 13 - Tweet Polarity and Subjectivity by Account Categories (Verified)

Figure 13 shows polarity and subjectivity across account type categories. Emergency services have the most positive tweets perhaps due to the aid nature of the account's tweets. Celebrities have the most negative tweets but all accounts still have an overall positive sentiment. Subjectivity across account types is nearly identical.

The overall sentiment score for both verified and non-verified tweets is positive: verified at 0.07 and non-verified at 0.06. It should also be noted that all accounts contained at least one (-1.0) sentiment score except *emergency services* which only went to (-0.33). The same can be observed in topic sentiment scores. All topics had at least one minimum score of (-1.0) except *aid / resources* with a low of (-0.43). This further shows that sentiment scores are less negative for *emergency services* and *aid / resources*.

4.3 When Do Verified Twitter Users Tweet About a Crisis Event?

As stated above, tweets about the Nor'easter began on February 28, 2018 and continued until the end of the storm on March 3rd. We have considered the accounts that made up verified tweets as well as the topics that were tweeted from those accounts for timeline visualization. To continue our understanding of the event and the role verified accounts have in crisis informatics, we will look at the data spread over the course of the storm.

4.3.1 User Categories Timeline

The number of tweets sent by each verified account type categories are compiled by hour over the course of the storm in the figure below.

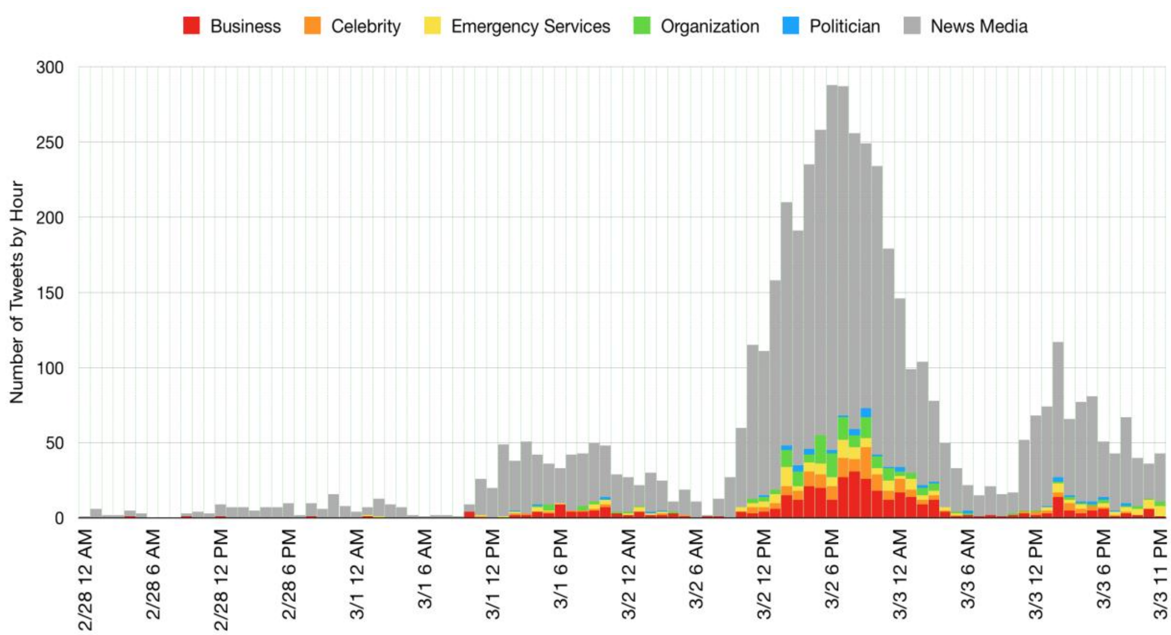

Figure 14 - Account Category Activity by Hour

The timeline of tweet activity in Figure 14, Figure 15, and Figure 16 is useful for visualizing the crisis event. There are several aspects of these figures worth noting. First, the timeline is mapped with a y-axis of number of tweets by hour which shows the true Twitter activity levels leading up to and during the storm (about the Nor'easter). The number of tweets sent is significantly more on March 2nd. The Nor'easter's low pressure that caused the most damage and storm activity formed on the night of March 1st and peaked late in the day of March 2nd.

As discussed in section 4.1, the *news media* account types acted first to raise awareness of the oncoming storm. It wasn't until the storm was active that other account types began tweeting in significant numbers. Looking at *politician* accounts we see their activity comes in the middle of the storm, perhaps reacting to constituents' needs or issuing official alerts as seen in section 4.2. Graphs showing individual categories over time are included in the appendix to this thesis. While *emergency services* and *politicians* did tweet on March 1, by March 2 it was at a much higher rate. All timeline analysis shows drops in activity levels at night and activity levels increase again in the day time.

4.3.2 Tweet Topic Timelines

The number of tweets sent by topic are compiled by hour over the course of the storm in the figure below as a stacked bar chart. Both verified (Figure 15) and non-verified (Figure 16) accounts are represented. Figure 17 and Figure 18 show the same data as Figure 15 and Figure 16 but in a percentage of topic by hour, instead of the number of tweets. This is also a useful comparison for visualizing topics over the course of the storm.

Figure 15 shows Twitter traffic by verified users surrounding the Nor'easter by topic. It shows the initial surge of *forecasts*, followed by various types of status updates (*damages*, *closures*, and other *statuses*) during the strongest part of the storm on March 2nd. Just like what was shown in Figure 10, the informative tweets are consistent leading up to the storm when more *entertainment* and *advertisements* begin. Figure 17 shows the data from Figure 15 but in percentages. Each column represents one hour and the percentages of tweet topics tweeted in that hour. Figure 16 and Figure 18 are identical representations but the data comes from non-verified accounts. There are less informative tweets coming from non-verified accounts and the timeline is more chaotic with regards to expecting certain kinds of data at points in the storm timeline. For example, we see on the non-verified accounts that *spam* is used early in the morning on March 1st while verified tweets are exclusively giving forecasts and warnings.

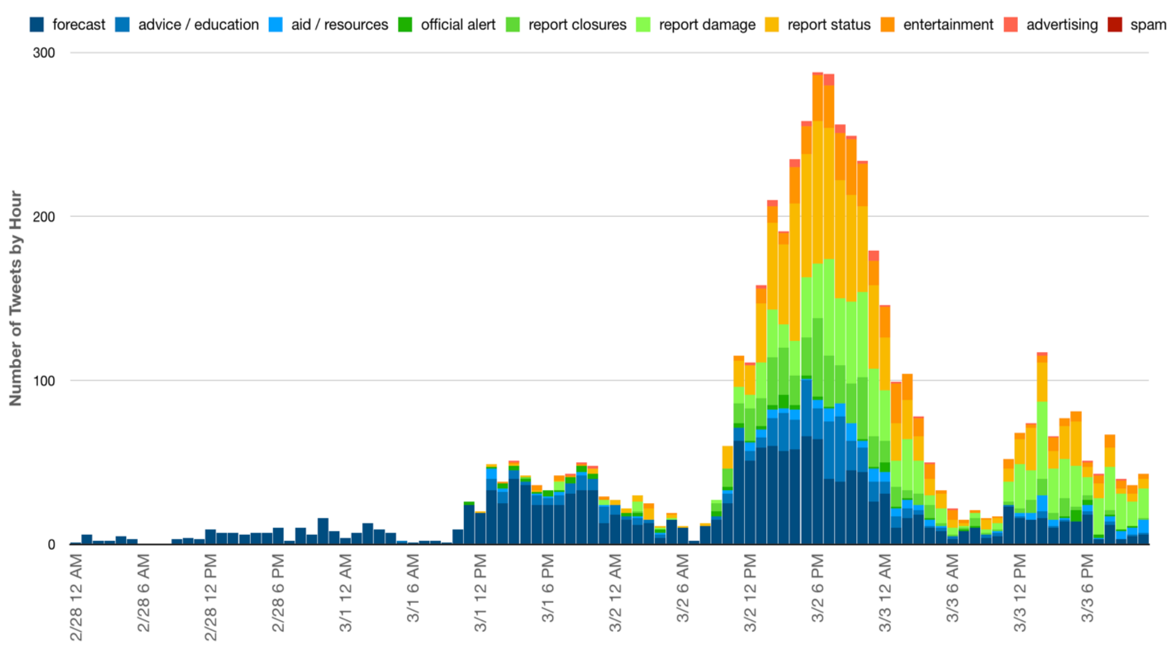

Figure 15 - Tweet Topic Activity by Hour (Verified)

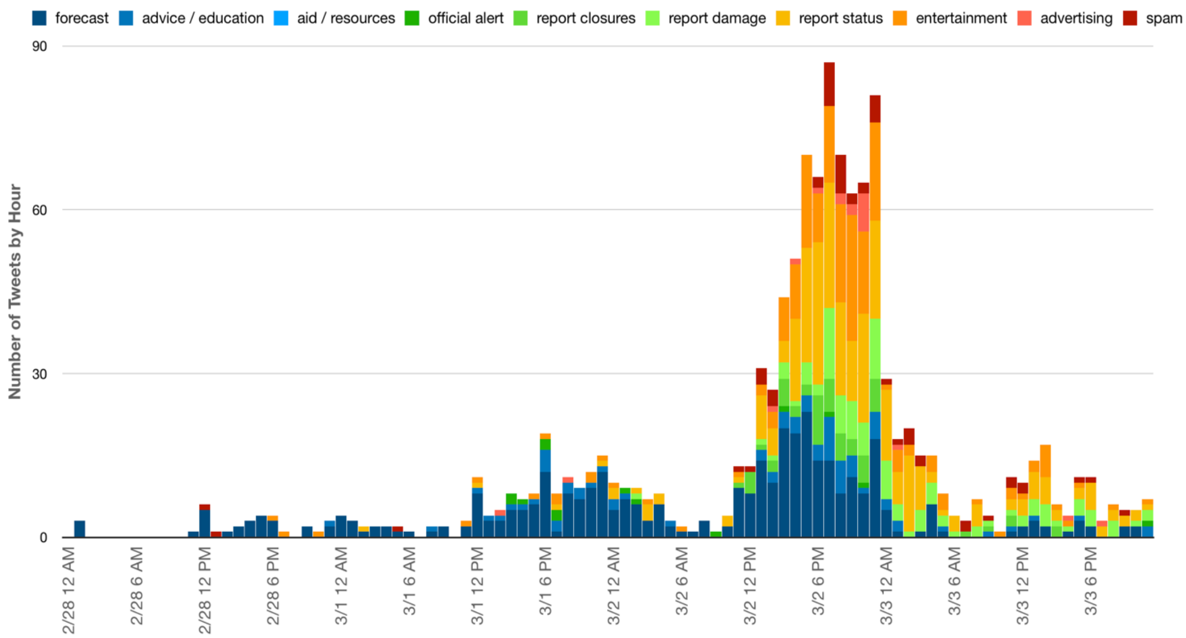

Figure 16 - Tweet Topic Activity by Hour (Non-verified)

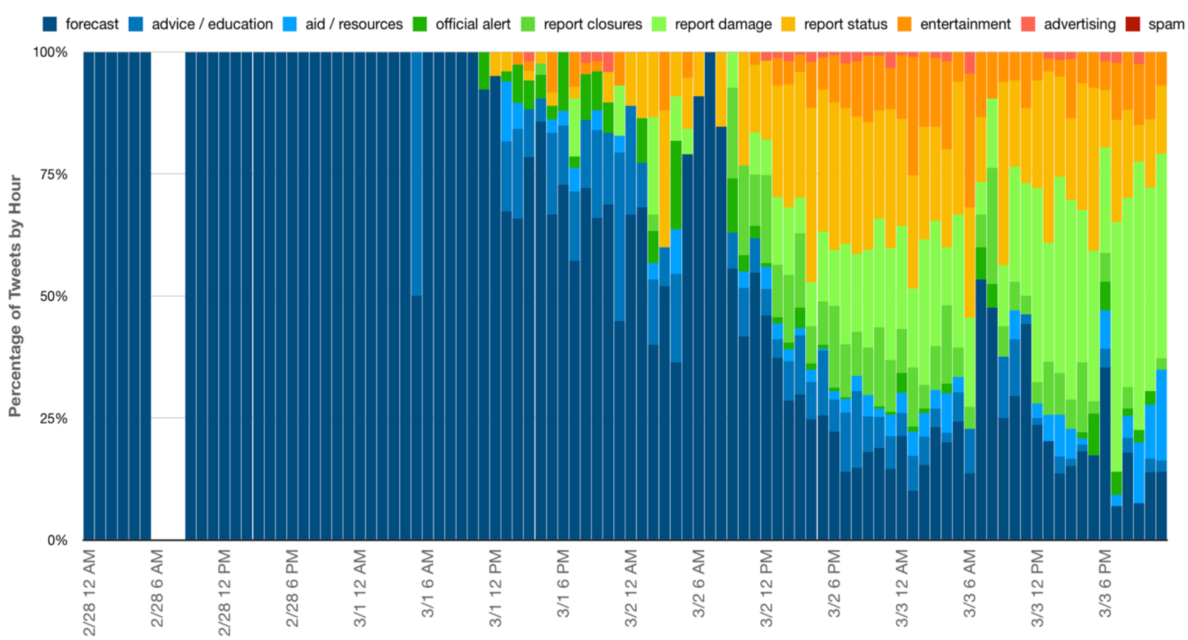

Figure 17 - Percentage of Tweet Topic by Hour (Verified)

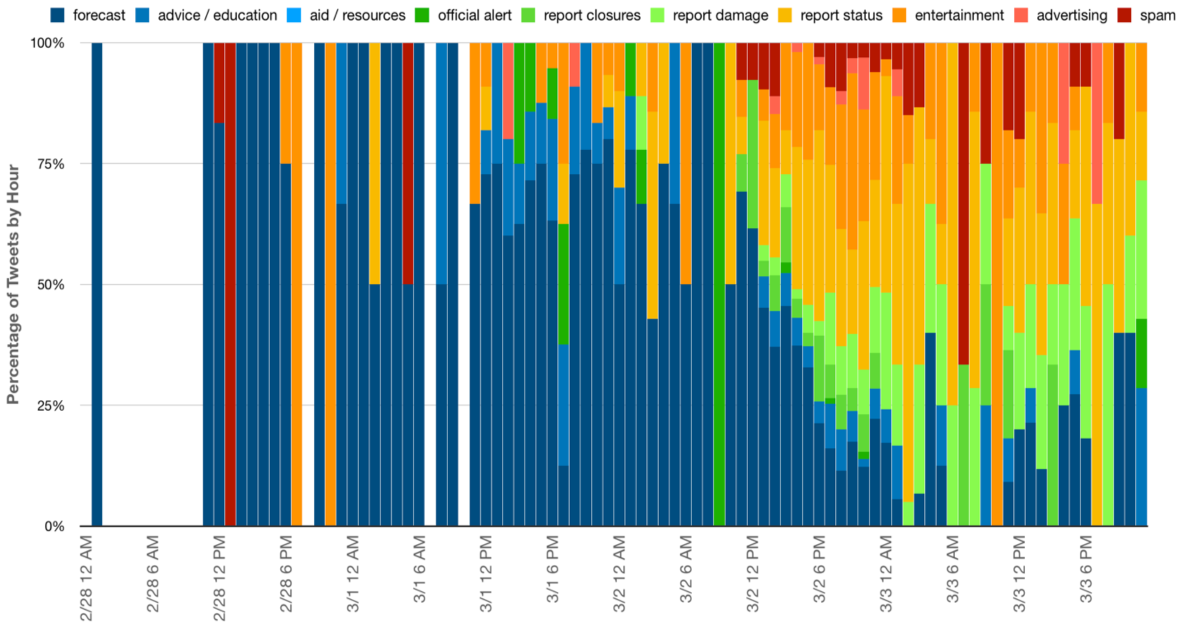

Figure 18 - Percentage of Tweet Topic by Hour (Non-verified)

CHAPTER 5

CONCLUSIONS

5.1 Thesis Summary

By answering our proposed research questions surrounding the use of verified Twitter accounts during crisis events, we are better able to visualize and understand this aspect of crisis informatics. Verified accounts represent a personal brand or organization and are seen to tweet more informative, on-topic information during the crisis event. Previous research looking critically at information credibility trends on Twitter found traits that exist in verified accounts lead to more credible information shared and is relevant to our findings [28]. We show that verified accounts stay on topic more often, tweet a higher percentage of informative tweets, have more positive sentiment in their messaging, tweet less spam, and tweet more original content regarding this Nor'easter crisis event.

5.2 Limitations

Data collection limitations exist in the Twitter API; whether paying Twitter for historical data, streaming real time data, or searching near history data, there are limitations. Twitter has a paid Historical Tweet API that allows the user to retrieve data all the way back to the first tweet but limits the number of requests made. To make reasonable observations a lot of data may need to be collected making research prohibitively expensive. Streaming data and the search API will not return every tweet, as some tweets are not indexed (distributed database issues) or removed for other reasons.

Other tweets may miss collection because of misspelling or lack of location information as scripts query the Twitter API for those fields.

The severity of the crisis event of study and other characteristics would likely change the data collection methodology. For the Nor'easter, the location was geographically too large for a location query using the Twitter API. With a smaller crisis, it would be possible to catch almost all tweets coming out of an area (if the tweets have location data). Limitations exist on both sides of the service, Twitter has limitations for collection and users limit what can be collected by not using trending words or not including location data in tweets. For example, if a user tweets "I'm freezing to death in my home," it will not be found by common keywords like storm, Nor'easter, help, crisis, etc. It may also not be seen by location queries if they do not tag a location.

Our methodology for data collection was based on the type of crisis event, size of event, and the trending status surrounding the event. The amount of data we obtained was sufficient to make observations within the limitations Twitter imposes.

5.3 Future Work

Because of the exploratory nature of this thesis and the proposed research questions, we expected to also uncover more questions as data was collected and analyzed. In order to stay on topic and relevant to our proposed questions, we analyzed data with the intent to answer the research questions directly. There are two avenues of future work related to this thesis 1) further analysis on our collected data and 2) similar analysis on other crisis event types.

5.3.1 Further Analysis on Nor'easter Data Collected

The amount of data returned by the Twitter API can be quite thorough (e.g., location data, time, retweet status, account statistics, etc.). While we did our best to answer the questions proposed, from the data collected there are several other questions that could be addressed:

- What type of content received the most retweets (relevant to the crisis event)?
- What user types and topic categories were favorited the most according to the Twitter API?
- Further breakdown of sub-categories; types of businesses, types of news media, types of organizations, types of entertainment tweets, etc.
- Location based questions. Where are these tweets coming from? Types of tweets mapped with location data. One limitation we found is very few tweets contained location data but almost all verified accounts had a location in the account description (at a higher rate than non-verified accounts).
- Retweet and organic retweet statistics mapped over time to understand when users are retweeting messages or creating original content in context of the storm timeline.

There are so many dimensions to the data collected that it would be difficult to address all questions or possible data comparisons in the space of one thesis. For example, location comparisons are difficult because only 1% of tweets we collected included location information and a larger data collection would be needed to see trends.

Looking at the data in several dimensions (time, user types, sentiment, tweet topic, etc.) can cause an overload of data to unpack in one thesis.

5.3.2 Analysis on Other Crisis Event Types

Beyond the data collected for this crisis event is the continued monitoring of future crisis events of different types. Based on two categories of crisis events we can look at natural events (fire, earthquake, flood, or another type of weather) or man-made crisis events (terrorist attacks, shootings, large commercial incidents, etc.). With spontaneous events, there is likely a different timeline of topics. For example, we would see less forecasts in a spontaneous event like an earthquake and possibly more damage reporting and aid resources. Sentiment analysis and categorizing informative topics was considered because those trends are more general to all crisis events where topic is more subjective to a specific event. The second category of crisis event is man-made events which would also produce different topic trends and may include more political bias. This type of event would likely need analysis on the accuracy of the information being tweeted to make further observations on verified Twitter accounts.

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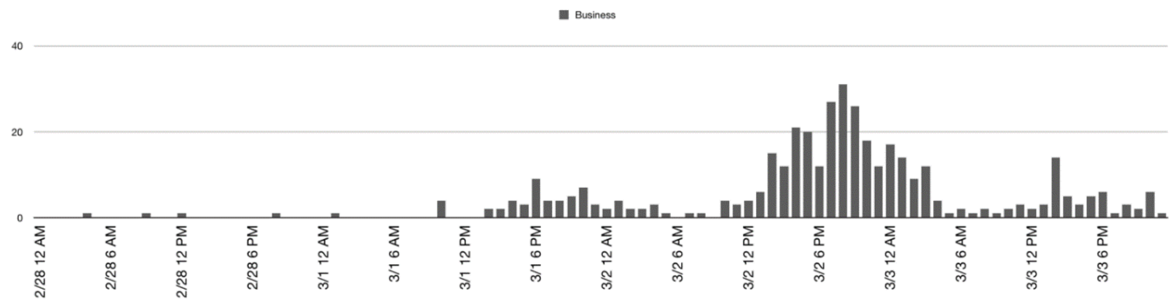
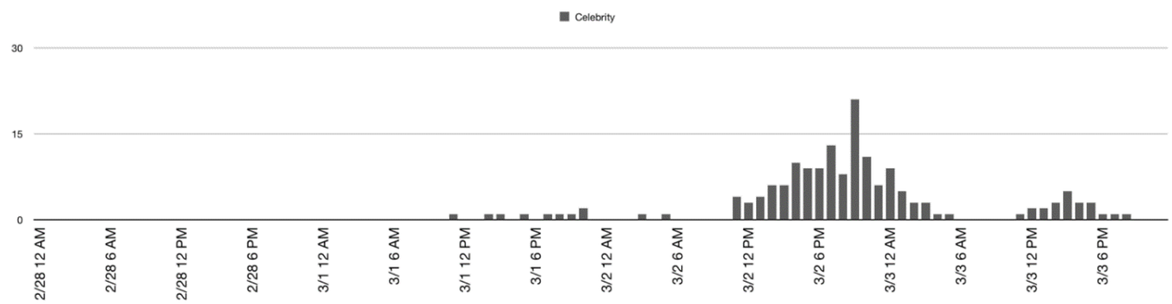
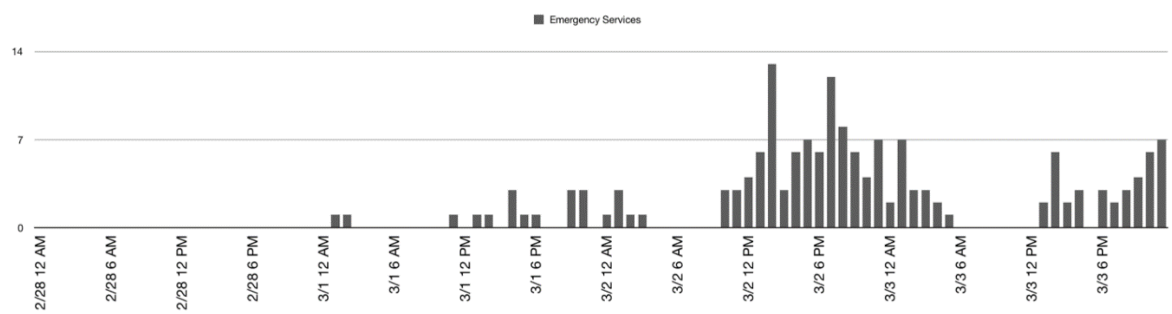
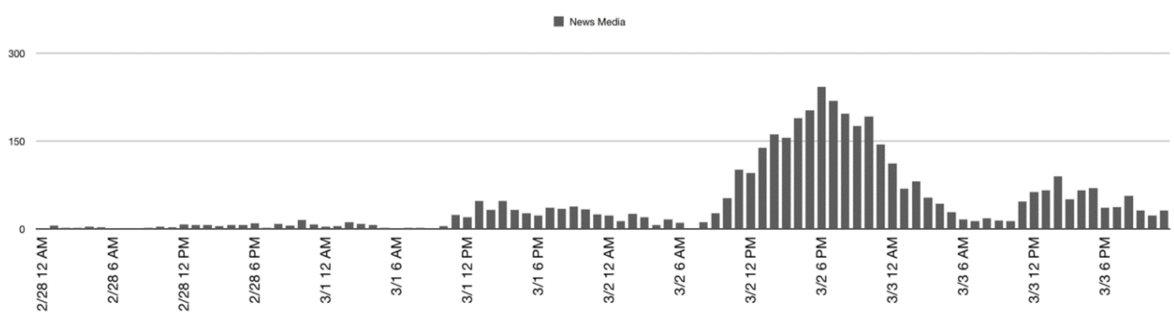
APPENDICES

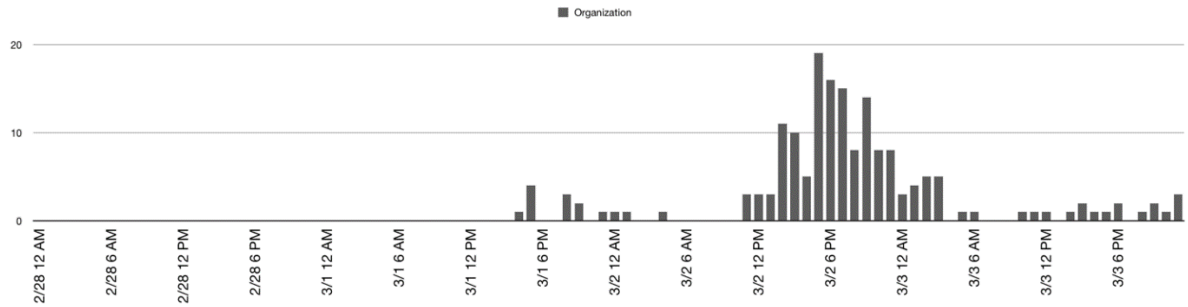
APPENDIX A: Verified User Category Activity Timelines










Organization
20
10
0
2/28 12 AM
2/28 6 AM
2/28 12 PM
2/28 6 PM
3/1 12 AM
3/1 6 AM
3/1 12 PM
3/1 6 PM
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3/2 6 AM
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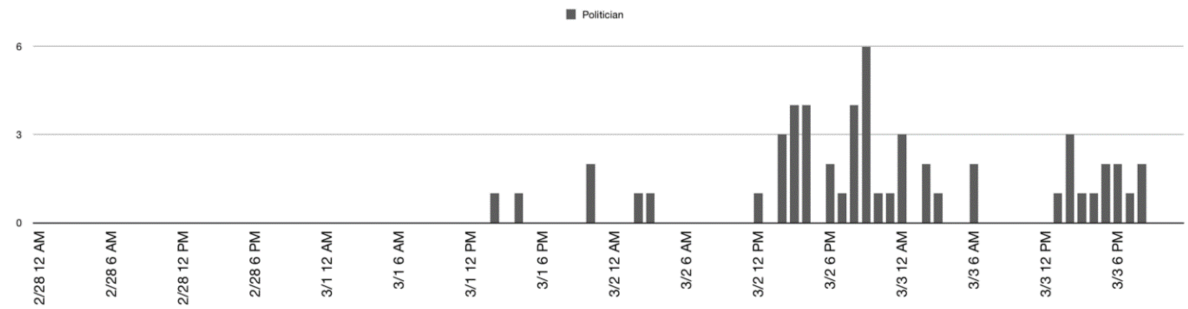
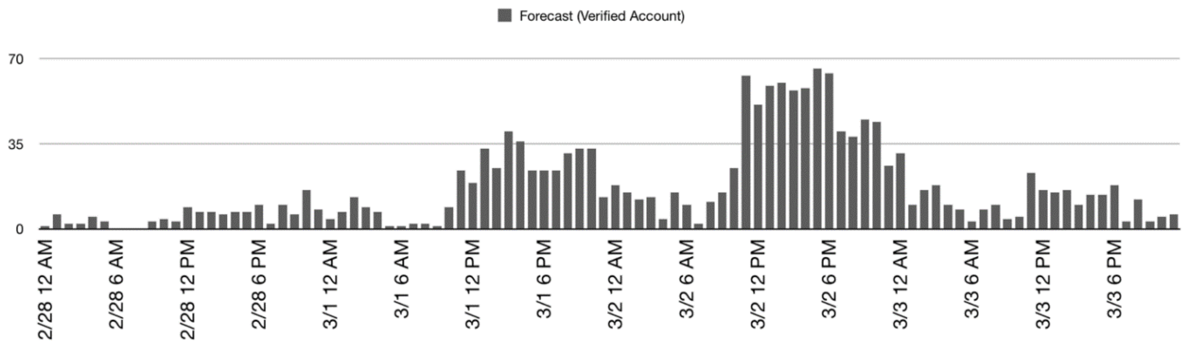
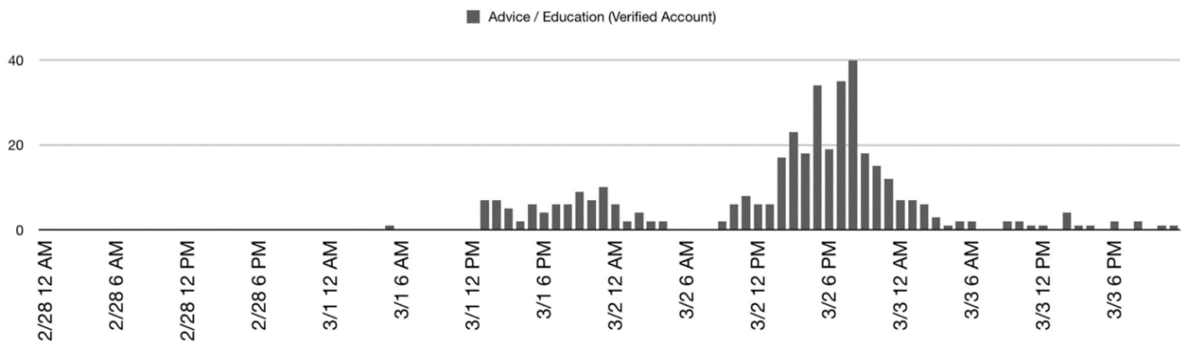
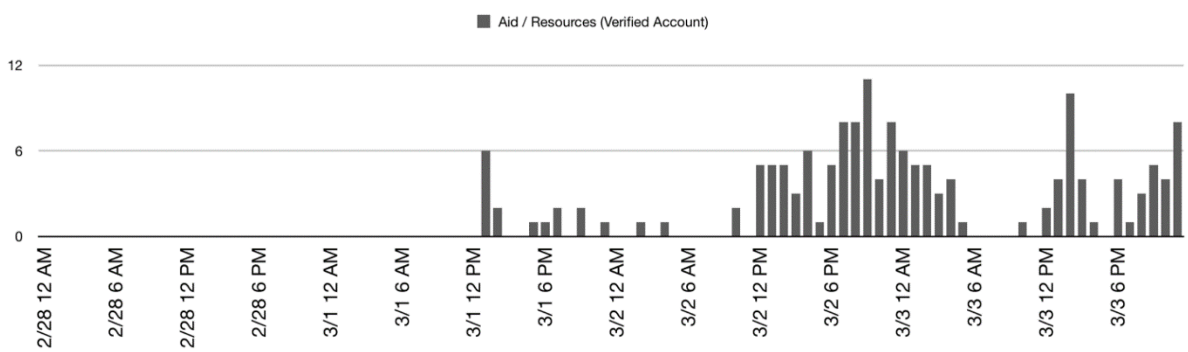
3/3 12 PM
3/3 6 PM

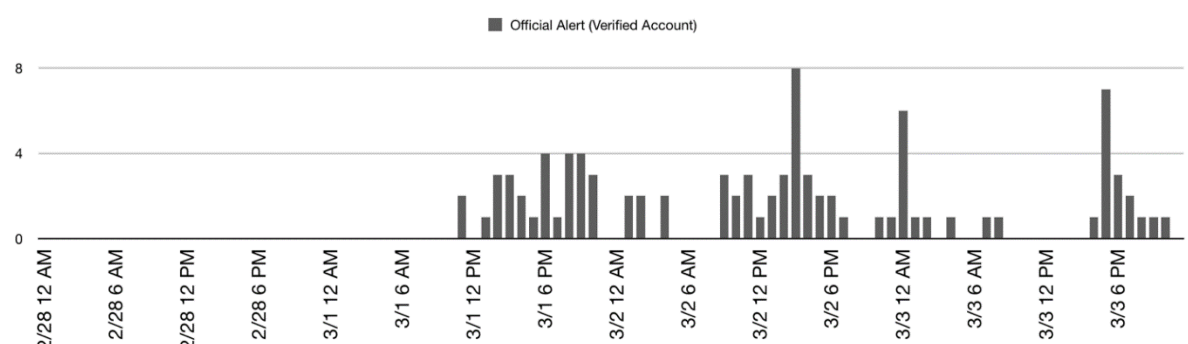

Politician
6
3
0
2/28 12 AM
2/28 6 AM
2/28 12 PM
2/28 6 PM
3/1 12 AM
3/1 6 AM
3/1 12 PM
3/1 6 PM
3/2 12 AM
3/2 6 AM
3/2 12 PM
3/2 6 PM
3/3 12 AM
3/3 6 AM
3/3 12 PM
3/3 6 PM

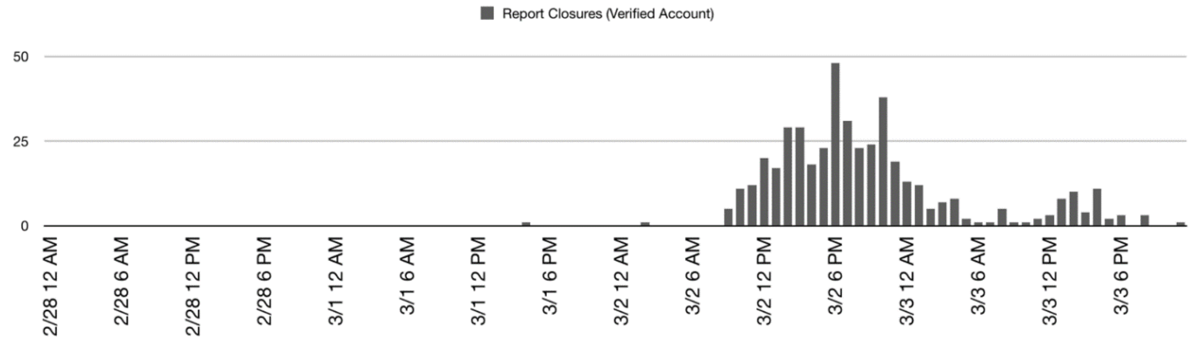
APPENDIX B: Topic Category Activity Timelines










Report Closures (Verified Account)
50
25
0
2/28 12 AM
2/28 6 AM
2/28 12 PM
2/28 6 PM
3/1 12 AM
3/1 6 AM
3/1 12 PM
3/1 6 PM
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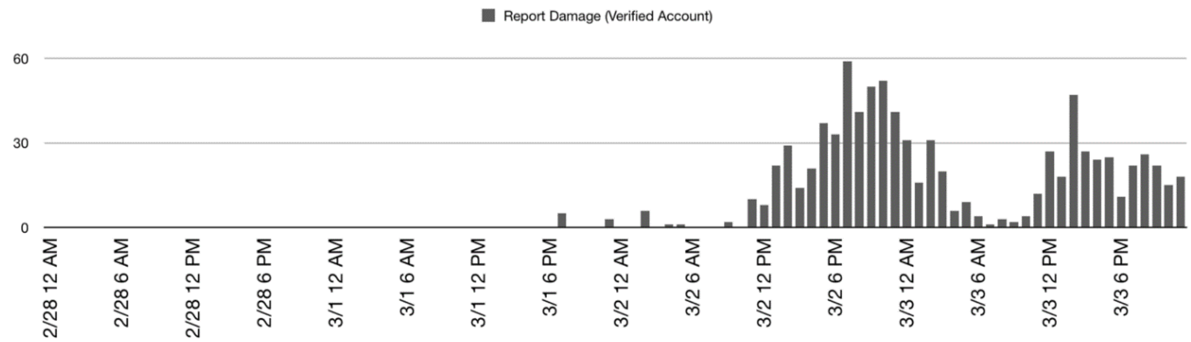
3/3 12 PM
3/3 6 PM


Report Damage (Verified Account)
60
30
0
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2/28 6 AM
2/28 12 PM
2/28 6 PM
3/1 12 AM
3/1 6 AM
3/1 12 PM
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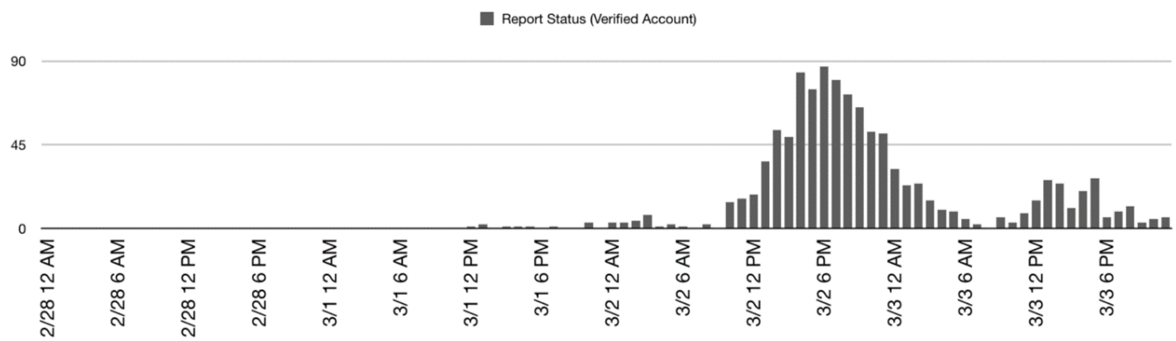
3/3 12 PM
3/3 6 PM


Report Status (Verified Account)
90
45
0
2/28 12 AM
2/28 6 AM
2/28 12 PM
2/28 6 PM
3/1 12 AM
3/1 6 AM
3/1 12 PM
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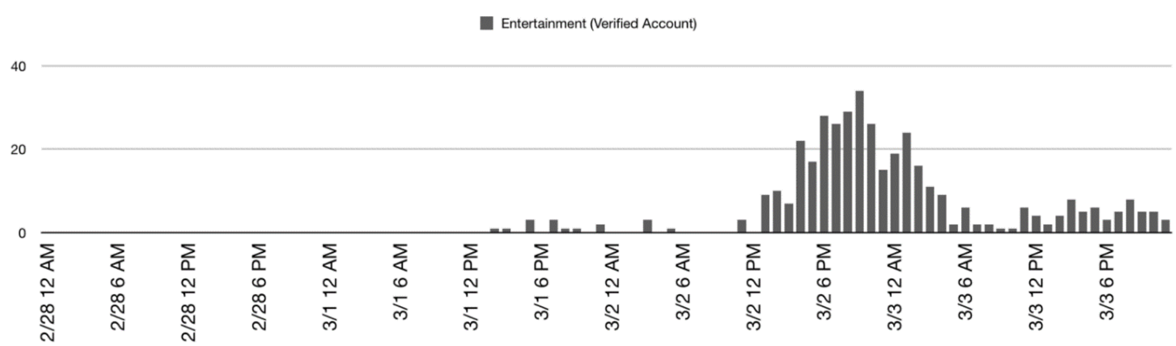
3/3 12 PM
3/3 6 PM


Entertainment (Verified Account)
40
20
0
2/28 12 AM
2/28 6 AM
2/28 12 PM
2/28 6 PM
3/1 12 AM
3/1 6 AM
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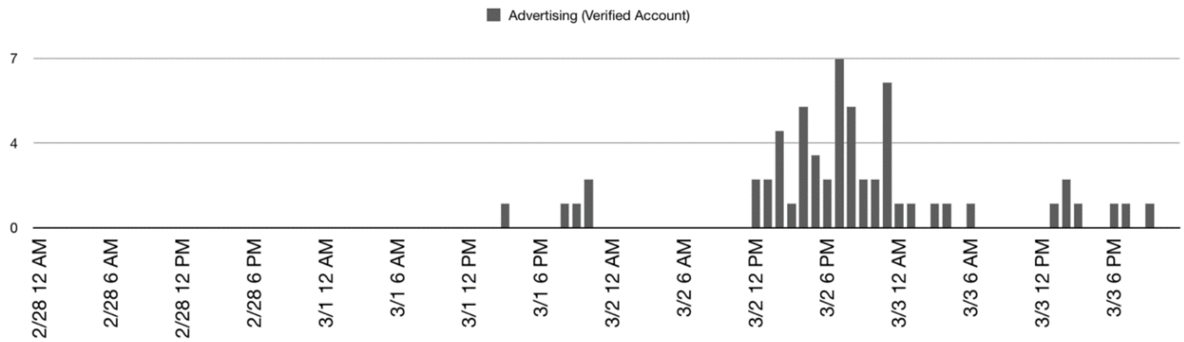
3/3 12 PM
3/3 6 PM



Advertising (Verified Account)
7
4
0
2/28 12 AM
2/28 6 AM
2/28 12 PM
2/28 6 PM
3/1 12 AM
3/1 6 AM
3/1 12 PM
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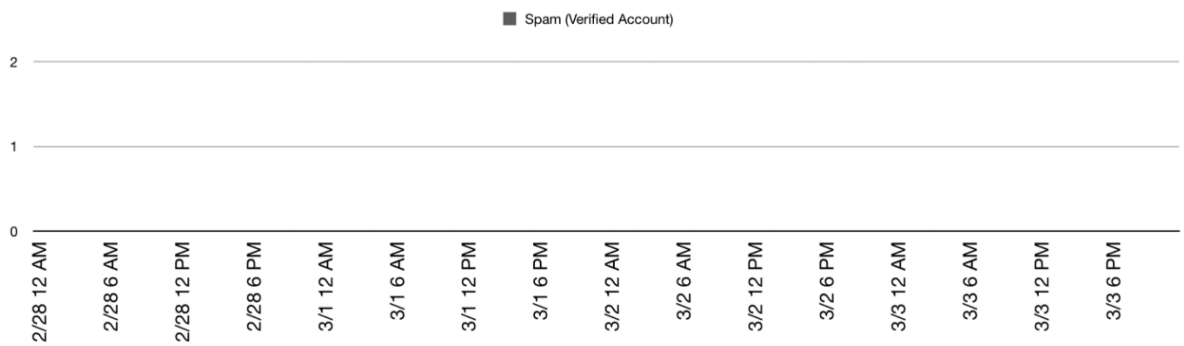
3/3 12 PM
3/3 6 PM



Spam (Verified Account)
2
1
0
2/28 12 AM
2/28 6 AM
2/28 12 PM
2/28 6 PM
3/1 12 AM
3/1 6 AM
3/1 12 PM
3/1 6 PM
3/2 12 AM
3/2 6 AM
3/2 12 PM
3/2 6 PM
3/3 12 AM
3/3 6 AM
3/3 12 PM
3/3 6 PM